HYDROLOGICAL PROCESSES
Hydrol. Process. **25**, 2211–2220 (2011)
Published online 9 February 2011 in Wiley Online Library
(wileyonlinelibrary.com) DOI: 10.1002/hyp.7976

Causes of systematic over- or underestimation of low streamflows by use of index-streamgage approaches in the United States†

Ken Eng,[1]* Julie E. Kiang,[2] Yin-Yu Chen,[3] Daren M. Carlisle[4] and Gregory E. Granato[5]

[1] *National Research Program, U.S. Geological Survey, Reston, VA 20192, USA*
[2] *Office of Surface Water, U.S. Geological Survey, Reston, VA 20192, USA*
[3] *U.S. Geological Survey, Reston, VA 20192, USA*
[4] *National Water-Quality Assessment Program, U.S. Geological Survey, Reston, VA 20192, USA*
[5] *U.S. Geological Survey, Northborough, MA 01532, USA*

Abstract:

Low-flow characteristics can be estimated by multiple linear regressions or the index-streamgage approach. The latter transfers streamflow information from a hydrologically similar, continuously gaged basin ('index streamgage') to one with a very limited streamflow record, but often results in biased estimates. The application of the index-streamgage approach can be generalized into three steps: (1) selection of streamflow information of interest, (2) definition of hydrologic similarity and selection of index streamgage, and (3) application of an information-transfer approach. Here, we explore the effects of (1) the range of streamflow values, (2) the areal density of streamgages, and (3) index-streamgage selection criteria on the bias of three information-transfer approaches on estimates of the 7-day, 10-year minimum streamflow ($Q_{7,10}$). The three information-transfer approaches considered are maintenance of variance extension, base-flow correlation, and ratio of measured to concurrent gaged streamflow (Q-ratio invariance). Our results for 1120 streamgages throughout the United States suggest that only a small portion of the total bias in estimated streamflow values is explained by the areal density of the streamgages and the hydrologic similarity between the two basins. However, restricting the range of streamflow values used in the index-streamgage approach reduces the bias of estimated $Q_{7,10}$ values substantially. Importantly, estimated $Q_{7,10}$ values are heavily biased when the observed $Q_{7,10}$ values are near zero. Results of the analysis also showed that $Q_{7,10}$ estimates from two of the three index-streamgage approaches have lower root-mean-square error values than estimates derived from multiple regressions for the large regions considered in this study. Published in 2011 by John Wiley & Sons, Ltd.

KEY WORDS bias; low streamflow; short-term streamgages; ungaged basins; intermittent streams; hydrologic similarity

Received 25 June 2010; Accepted 2 December 2010

INTRODUCTION

Low-flow characteristics, such as the 7-day, 10-year low flow $Q_{7,10}$ (Riggs, 1980), are often used by state and local water managers as indirect regulatory controls on surface–water quality in the United States. These characteristics are often required for ungaged basins and for partial-record streamflow sites (henceforth referred to as partial-record streamgages). The streamflow record at a partial-record streamgage can be defined as a collection of sporadic discharge measurements (often <20).

Multiple linear regressions are often used to estimate low-flow characteristics for ungaged basins or partial-record streamgages (Thomas and Benson, 1970; Eng and Milly, 2007). Regressions form a relationship among the low-flow characteristics of interest and basin attributes, such as drainage area, A_d. An alternative to regressions is the index-streamgage approach, which generally consist of three steps: (1) selection of streamflow information [e.g. range of discharges and (or) time period of interest], (2) definition of hydrologic similarity and selection of index streamgage, and (3) application of an information-transfer approach, such as maintenance of variance extension (MOVE) (Hirsch, 1982), base-flow correlation (BFC) (Stedinger and Thomas, 1985), and Q-ratio invariance (QRI) (Potter, 2001). The three information-transfer approaches are based on establishing an invariant relationship over the range of all selected streamflow values between a partial-record and an index streamgage. These index-streamgage approaches have been used in many studies (Dingman and Putscher, 1991; Ries and Friesz, 2000; Reilly and Kroll, 2003; Laaha and Blöschl, 2005; Funkhouser *et al*., 2008) and their results can be compared to those estimated by multiple linear regressions (Laaha and Blöschl, 2005).

A few studies have found that estimates of low-flow characteristics from index-streamgage approaches are either systematically over- or underestimated (i.e. biased) (Stedinger and Thomas, 1985; Dingman and Putscher, 1991). A potential source of the bias may be associated with the first step in the application of index-streamgage approaches, which is selection of the seasonality or range

* Correspondence to: Ken Eng, National Research Program, U.S. Geological Survey, Mail Stop 430, Reston, VA 20192, USA.
E-mail: keng@usgs.gov

of variation of streamflow values. Another two sources could be linked to the second step: the criteria used to select an index streamgage and the availability of index streamgages as measured by the areal density of surrounding streamgages. An inherent bias associated with the information-transfer approaches could be another source of bias. These potential sources are not mutually exclusive from one another.

A topic that has received little attention in the literature is the impact of the range of streamflow values on the bias of estimated low-flow characteristics by the index-streamgage approach. The user assumes that a linear or log–linear relationship among the concurrent streamflows is valid over the entire range of these values when applying the information-transfer approaches, such as MOVE, BFC, and QRI. This assumption may be justified when an index streamgage is located within several kilometres upstream or downstream of a partial-record streamgage of interest, and if there are no substantial differences in physiographic and anthropogenic activities that occur between them. This assumption, however, is often violated when the partial-record streamgage and index streamgage are located on different streams because of differences in streamflow generation processes between both basins. A suggested practice is to include a few 'high base-flow values' in the range of considered streamflow values to improve the slope of the relationship among concurrent streamflow values (United States Geological Survey, 1979). Increasing the range of streamflow values will increase the likelihood of violating the assumption of an invariant relationship across this range. A few previous studies (Dingman and Putscher, 1991; Reilly and Kroll, 2003) limit their analysis to a seasonally defined 'low-flow' period. This limitation does not directly control the range of streamflow values and as a consequence the relationship among concurrent streamflows may change substantially over this range.

Dingman and Putscher (1991) found that the bias was not dependent on the degree of basin-attribute similarity. The areal density of the streamgage network, however, is another issue that has received little attention (Dingman and Putscher, 1991). This areal density could be a source of bias in the index-streamgage approaches, as the choice of index streamgages will be more limited in streamgage networks with lower densities than it would be for streamgage networks with higher densities.

Our objectives are to explore the effects on bias of (1) the range of streamflow values used in the analysis, (2) the areal density of a streamgage network, and (3) two index streamgage selection criteria: maximum Pearson correlation coefficient and hydrologic similarity measured by basin attributes. As a baseline for comparison, multiple linear regression results are compared to those of the index-streamgage approach. This exploration is based on synthetic partial-record streamgages generated by random sampling of data from 1120 streamgages across the conterminous United States.

STUDY AREA

A preliminary set of 1494 streamgages spread across the conterminous United States was used in this study. A somewhat smaller subset of these streamgages was ultimately used, as discussed in the following section. These streamgages are minimally impacted by anthropogenic influences as defined by a quantitative metric and best professional judgment described by Falcone *et al.* (2010) and have at least 20 years of streamflow record. The size of basins ranged from 1·6 to 25 791 km^2, with a median of 241·8 km^2.

We split the streamgages into three groups defined by their geographic location for analysis: east, central, and west. The Mississippi River provided the boundary between the east and the central regions. The boundary between the central and west regions is subjectively defined along the eastern state borders of Montana, Wyoming, Colorado, and New Mexico, as shown in Figure 1, based on the low streamgage density along these borders. The resulting number of streamgages in the east, central, and west regions is 624, 307, and 563, respectively.

DATA AND SYNTHETIC PARTIAL-RECORD MEASUREMENT GENERATION

A subset of the 228 basin attributes defined by Falcone *et al.* (2010) is used in this study, which mostly pertain to climate, hydrology, hydrologic modifications and dams, land cover, soils, and topography. We exclude basin attributes that are qualitative, point estimates, water-quality descriptors, or ecological descriptors. We use the remaining basin attributes as criteria for hydrologic similarity for index-streamgage approaches (see Section on Selection of Index Streamgages) and as predictor variables in multiple linear regressions (see Section on Multiple Linear Regression).

For each streamgage, the observed $Q_{7,10}$ value is calculated by fitting a log-Pearson type III distribution to the annual time series of minimum 7-day average streamflows (Tasker, 1987). The annual time series is based on the climatic year (1 April to 31 March). For annual time series that have one or more values equal to zero, we apply a conditional probability adjustment. If an observed $Q_{7,10}$ value is equal to zero, the corresponding streamgage is excluded from this study, because the MOVE and BFC approaches require a log (base 10) transformation of the low-flow characteristics. The number of streamgages with observed $Q_{7,10}$ values equal to zero are 83, 175, and 116 for the east, central, and west regions, respectively. The final numbers of streamgages used in this study are 541, 132, and 447 for the east, central, and west regions, respectively, and their locations are shown in Figure 1.

The 50, 75, 80, 90, and 100% exceedance-probability streamflows (streamflow values that are equalled or exceeded, say 90% of the time) are calculated using the entire daily-streamflow record for each streamgage (Searcy, 1959). The daily-streamflow values are ranked

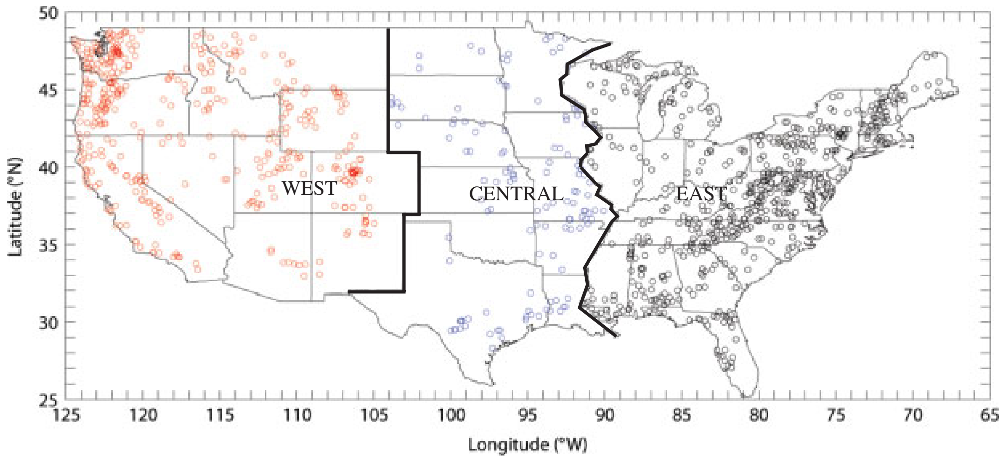

Figure 1. Circles represent the 1120 continuous streamgages used in this study. Black is for the streamgages in the east region, blue for the central region, and red for the west region of the United States

from largest to smallest and a probability is calculated for each value based on the California-plotting position (Loaiciga, 1989). The probabilities are insensitive to the choice of plotting position due to the large number of daily-streamflow values in each record, so we do not consider other plotting positions. If needed, interpolation between two probabilities and their associated streamflow values is used to obtain streamflow for a specified exceedance-probability value. We use the streamflow associated with the 50, 75, 80, 90, and 100% exceedance probabilities in the generation of synthetic partial-record measurements that are described below (henceforth these streamflow values are referred to as percent–exceedance–probability streamflows).

Each streamgage is treated, in turn, as a partial-record streamgage. Generation of synthetic partial-record measurements is simulated by random sampling as described by Eng and Milly (2007) and summarized here. First, all recession segments (sequences of decreasing daily-streamflow values) of 8 days or longer are identified from the daily-streamflow record for all climatic years. From a randomly chosen (with replacement) recession segment, we truncate the first 5 days and then randomly choose one of the remaining days as a synthetic partial-record measurement. We use only recessions of 8 days or longer, because we are trying to estimate a low-flow characteristic. In this study, we use an additional step that selects a measurement that is bounded by a specified range of streamflows defined by the exceedance-probability values. To explore the sensitivity of the range of streamflow values on the performance, we test four different ranges: 50–100, 75–100, 80–100, and 90–100% exceedance probability. The United States Geological Survey (1979), Dingman and Putscher (1991), and Zhang and Kroll (2007) suggest different minimum numbers of partial-record measurements that range from 6 to 12, so we use a value equal to 10 in this study. These measurements are collected over a span of a few years. We perform the sampling described above 500 times for each range of streamflow considered at each streamgage to obtain robust error statistics. Each set of ten synthetic measurements is henceforth termed a partial record.

We estimate base-flow recession time constant, τ, values at partial-record streamgages following the methods from Eng and Milly (2007), which are summarized here. To estimate τ, a second (different) streamflow value is randomly sampled from each recession segment. For every pair of streamflow values, an estimate of τ is calculated by

$$\tau = \frac{J\Delta t}{\ln Q_j - \ln Q_{j+J}} \quad (1)$$

where Q_j is the streamflow on day j, J the lag measured in days between the two Q values, and Δt the length of 1 day. Thus, 500 estimates of τ are calculated and for each streamgage, we compute a 'large-N' estimate of τ as the average of 500 such estimates. This process is done for the four different ranges of streamflow values considered in this study, which results in four large-N estimates of τ at each streamgage. The large-N estimates are used to calculate the parameters of multiple linear regressions when τ is included as a potential predictor (Eng and Milly, 2007).

We use the median geographic distance of the ten closest streamgages to a synthetic partial-record streamgage, G, as a measure of the areal density of streamgages. Small values of this metric are associated with more candidate index streamgages located geographically close to the partial-record streamgage. The value of ten is chosen subjectively. This chosen value has small impact on our analysis, as our interest is to analyse the relative impact of variations in the density of streamgage networks on the bias of estimated $Q_{7,10}$ values for partial-record streamgages.

SELECTION OF INDEX STREAMGAGES

An index streamgage is chosen from a subset of streamgages in the same region (east, central, or west) as the partial-record streamgage. A common 10-year overlap period in all streamflow records is required for all streamgages in the subset and the partial-record streamgage. This 10-year overlap helps to ensure that there is sufficient data to create random samples for the synthetically generated partial records. In addition, a 10-year overlap may help to ensure that the statistics calculated at each gage are sufficiently influenced by similar events (Kennard *et al.*, 2010).

The index streamgage is selected by two measures of similarity between the partial-record and index streamgages: (1) maximization of the Pearson correlation coefficient, ρ, of the ten concurrent $\log(Q)$ values between the streamgages and (2) minimization of differences in basin attributes. The difference in basin attributes is defined as the weighted distance between streamgages in a Euclidean space whose dimensions are normalized basin attributes (Laaha and Blöschl, 2005). The basin attributes used for each region were selected as part of the development of the multiple linear regression equations for each region (see Section on Multiple Linear Regression).

The distance with respect to weighted basin attributes between streamgages i and j is

$$R_{ij} = \left[\sum_{k=1}^{n} C_k \left(\frac{\log \omega_{ki} - \log \omega_{kj}}{\sigma_{\log \omega_k}}\right)\right]^{1/2} \tag{2}$$

where ω_k is the kth selected basin attribute, $\sigma_{\log \omega_k}$ the global (i.e. whole region) standard deviation of the kth basin attribute, and C_k the weight for the kth basin attribute and all weights sum to a value of one. The C_k weight is the fraction of the total t value for the kth basin attribute. The total t values are equal to the sum of all t values associated with all statistically significant basin attributes in a multiple linear regression for each region excluding the constant. These predictors are also used in Equation (2) for each region. An additional constraint applied both to ρ and basin attributes criteria is that the index streamgage be no farther than 200 km from the partial-record streamgage; however, if all streamgages are farther than 200 km from the partial-record streamgage, then we select the closest streamgage to be the index streamgage, regardless of the R_{ij} values. We use a geographic distance of 200 km as suggested by Reilly and Kroll (2003).

MULTIPLE LINEAR REGRESSION

For each region, we assume a model of the form

$$\log Q_{7,10} = \beta_0 + \sum_{k=1}^{n} \beta_k \log \omega_k + \delta \tag{3}$$

where ω_k represents the significant predictors, β_k the regression parameters, and δ the model error. Four regression models were formed in each region, because τ values are estimated from four different ranges of streamflow values. Each regression considered an initial pool of predictors consisting of the 228 basin attributes by Falcone *et al.* (2010) and one of the four large-N τ values. We perform a step-wise multiple linear regression fit separately for each region using these initial pools of potential predictors. Only predictors with t values >2 or <-2 are accepted. For each region, we then remove (1) the predictors whose significance would vanish if another significant predictor was removed and (2) predictors that are strongly correlated with other predictors. These removals were to reduce the problem of multicollinearity (Montgomery *et al.*, 2001) in the regressions that exist among highly correlated predictors. The final predictors used in each region are listed in Figure 2.

ESTIMATION OF LOW-FLOW CHARACTERISTICS AT PARTIAL-RECORD STREAMGAGES

Multiple linear regressions

We apply the multiple linear regression to each synthetic partial-record streamgage 500 times for every range of streamflow values considered. For each application, the value of τ is estimated as the arithmetic average of the ten estimates of τ associated with the ten measurement pairs within the specified range of streamflow values in the partial record.

QRI approach

QRI for estimation of base flow (Potter, 2001) can be extended to estimate $Q_{7,10}$ at partial-record streamgages by

$$Q_{7,10} = W Q_{7,10(I)} \tag{4}$$

where $Q_{7,10(I)}$ is the estimate at the index streamgage and W is given by

$$W = \frac{1}{L} \sum_{j=1}^{L} \frac{Q_j}{Q_{j(I)}} \tag{5}$$

where L is the number of streamflow values at the partial-record streamgage (=ten chosen in this study), Q_j the jth streamflow at the partial-record streamgage, and $Q_{j(I)}$ the jth concurrent streamflow at the index streamgage.

MOVE approach

MOVE (Hirsch, 1982) fits a line of organic correlation to concurrent partial-record streamgage and index-streamgage $\log(Q)$ values. The line of organic correlation minimizes the sum of areas of right triangles that are formed when a vertical and a horizontal line are extended from each measurement to the fitted line in a log–log scatter plot. The MOVE estimate of $Q_{7,10}$ obeys

$$\log Q_{7,10} = \overline{\log Q} + \frac{S_Q}{S_{Q_I}} (\log Q_{7,10(I)} - \overline{\log Q_I}) \tag{6}$$

where $\overline{\log Q}$ is the arithmetic mean of the $\log(Q)$ values at the partial-record streamgage, $\overline{\log Q_I}$ the corresponding quantity for concurrent streamflow values at the index streamgage, S_Q the standard deviation of the $\log(Q)$ values at the partial-record streamgage, and S_{Q_I} the corresponding quantity at the index streamgage. This approach

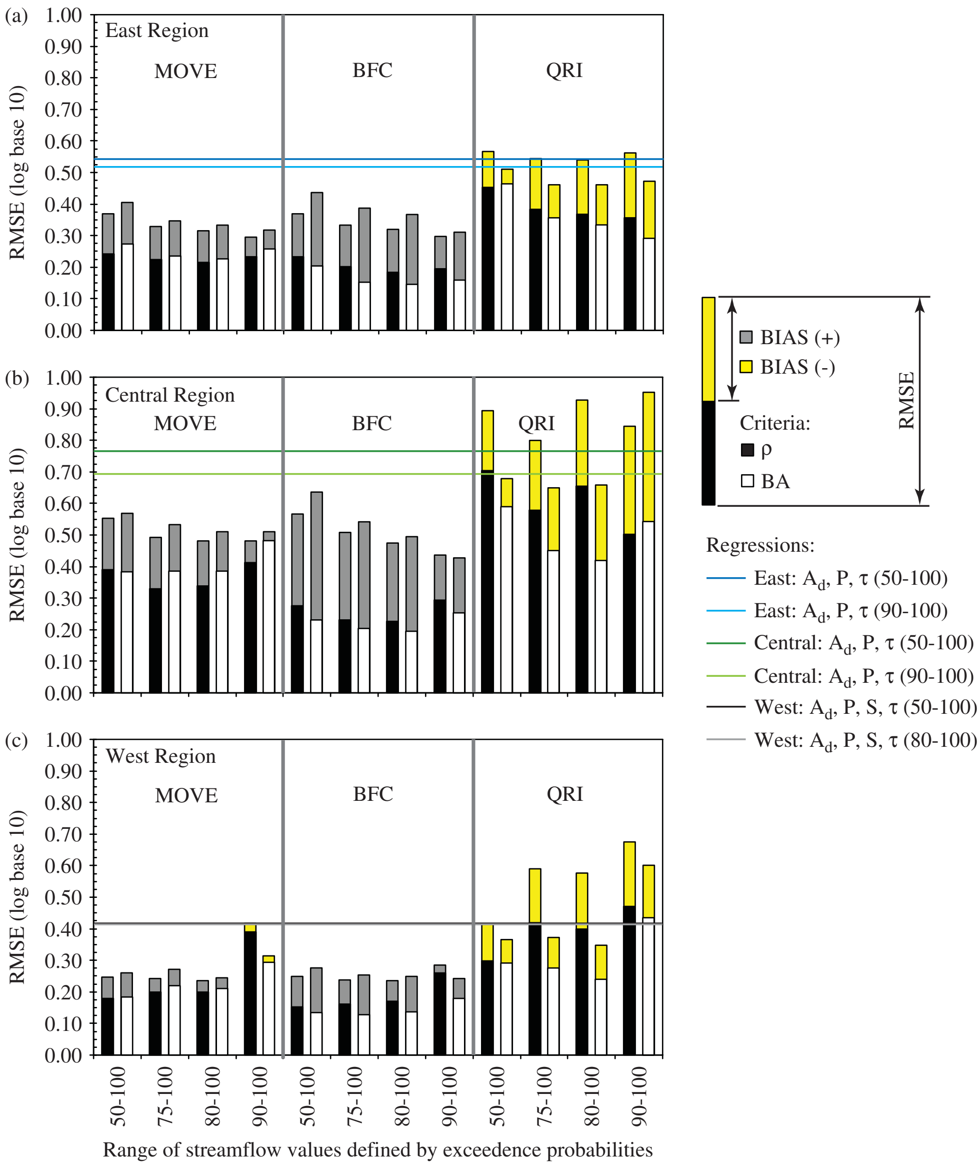

Figure 2. Plot of the RMSE and BIAS values for index-streamgage approaches using MOVE, BFC, and QRI for the east, central, and west regions. The full height of the bars represents the total RMSE errors; the BIAS values are represented as a fraction of the total RMSE values. The different coloured lower portions of the bars indicate the two index-streamgage selection criteria used: maximum Pearson correlation coefficient, ρ, and basin attributes, BA. The horizontal lines are used to represent the RMSE of multiple linear regressions using A_d, drainage area; P, mean annual precipitation; S, mean snow percentage of total precipitation; and τ, the base-flow recession time constant as predictor variables. The values in parentheses represent the range of streamflow values used to calculate τ

is applicable when there are ten or more concurrent observations (United States Geological Survey, 1985).

BFC approach

The BFC approach (Stedinger and Thomas, 1985) estimates low-flow characteristics by

$$\log Q_{7,10} = \mu_p + K_p \sigma_p \tag{7}$$

where μ_p is the estimated mean of annual time series of minimum 7-day average streamflow at the partial-record streamgage, σ_p the estimated standard deviation of the annual time series of minimum 7-day average streamflow at the partial-record streamgage, and K_p the log-Pearson type III standard deviate for a recurrence interval of 10 years at the partial-record streamgage, which is assumed to equal the K value from the chosen index streamgage. The K value is also a function of the skew of the annual time series. The μ_p and σ_p are

$$\mu_p = \beta_1 + \beta_2 m_I \tag{8}$$

$$\sigma_p = \left\{ \beta_2^2 s_I^2 + s_e^2 \left[1 - \frac{s_I^2}{(L-1)s_c^2} \right] \right\}^{1/2} \tag{9}$$

where m_I is the mean of the annual time series of minimum 7-day average streamflow values at the index streamgage, ${s_I}^2$ the variance of the annual time series at the index streamgage, ${s_c}^2$ the variance of the concurrent streamflow values at the index streamgage, β_1 and β_2 the constant and coefficient of an ordinary least-squares regression among concurrent streamflow values at the partial-record and index streamgages, and $s_e{}^2$ the squared standard error from the ordinary least-squares regression. This approach is dependent on the number of available base-flow measurements at the partial-record streamgage.

Performance metrics

The performance metrics, we use in this study, are based on the residual error for the ith partial-record streamgage for the jth data set that is given by

$$e_{ij} = \log\left(\hat{Q}_{7,10}\right)_{ij} - \log\left(Q_{7,10}\right)_i \tag{10}$$

where $\log\left(\hat{Q}_{7,10}\right)$ values are the estimated $\log(Q_{7,10})$ values from either the multiple linear regressions or the index-streamgage approach.

The root-mean-square error (RMSE) value is used to evaluate the performance of multiple linear regressions and index-streamgage approach. The RMSE values are calculated by

$$\mathrm{RMSE} = \left(\frac{1}{nk}\sum_{i=1}^{n}\sum_{j=1}^{k} e_{ij}^2\right)^{1/2} \tag{11}$$

where n is equal to the number of streamgages in a region and k is equal to the number of data sets (= 500).

The BIAS values are used to evaluate the tendency of the index-streamgage approach to either systematically over- or underestimate the observed $\log(Q_{7,10})$ values. The BIAS is calculated by

$$\mathrm{BIAS} = \frac{1}{nk}\sum_{i=1}^{n}\sum_{j=1}^{k} e_{ij} \tag{12}$$

Positive values of the BIAS indicate a systematic overestimation of the observed $\log(Q_{7,10})$ values and negative values indicate an underestimation.

The percentages of 'failed' applications of the index-streamgage approach are also calculated. The criteria we use to define a failed application are either (1) if an e_{ij} value exceeds 10 or is <-10 or (2) if all the streamflow values at either the partial-record and/or index streamgage are equal. From the remaining applications that did not fail, we calculate another percentage of applications of the index-streamgage approach that resulted in an e_{ij} value that equalled or exceeded the RMSE value for the multiple linear regression in each region.

RESULTS

The average RMSE and BIAS for the various experimental runs are shown in Figure 2. The MOVE and BFC approaches, with the exception of one case in the west, consistently overestimate $\log(Q_{7,10})$ values; in contrast, the QRI approach consistently underestimates the $\log(Q_{7,10})$. In general, the application of MOVE and BFC to a restricted range of streamflow values substantially reduces BIAS in all regions. Reductions in RMSE accompany these decreases in BIAS, with the largest reductions in the east and central regions. An additional benefit to decreasing the range of streamflow values when using MOVE or BFC is that the likelihood of calculating an extreme outlier from the index-streamgage approach is substantially reduced roughly by half in the east and central regions; however, there are only modest reductions in the west region. In contrast, the BIAS increases for the QRI approach when the range of streamflow values used is reduced.

The BIAS when using MOVE is not significantly affected by whether index streamgages are selected based on the maximum Pearson correlation coefficient or similarity of basin attributes (Equation (2)). The BFC approach, however, shows somewhat lower BIAS when using the maximum Pearson correlation coefficient than with basin-attribute similarity. The QRI approach shows lower BIAS values when using basin-attribute similarity.

The 500 e_i values from the applications of the index-streamgage approach using MOVE, BFC, and QRI are averaged at each partial-record streamgage for each index-streamgage selection method. These average residual errors are plotted against G, our metric for the areal density of streamgages at each location, and shown in Figure 3. Results from all the three regions are combined. For MOVE and BFC, the magnitude and sign of e_i show no significant dependence on the value of G. The median e_i values are invariant to G values, but the inter-quartile range (IQR = 75th–25th quartile) increases as the network becomes less dense. These two approaches are equally likely to produce an extreme residual in dense and sparse portions of the streamgage network. For the QRI approach, the extreme outlying residuals tend to become more negative (underestimation) for sparser networks than for denser networks. Using either the maximum Pearson correlation coefficient or Equation (2) to select an index streamgage has little impact on the results shown in Figure 3 except for the QRI approach.

The regional arithmetic mean and standard deviation of the Pearson correlation coefficient values among the concurrent streamflow values are reported in Table I. The largest regional Pearson correlation coefficient values are associated with the largest range in streamflow values and vice versa for small Pearson correlation coefficient values. The spread in the Pearson correlation coefficient values increases considerably as the streamflow range becomes more restricted. The 500 Pearson correlation coefficient values for each partial-record streamgage are averaged and compared to the residuals for applications of the index-streamgage approach using MOVE, BFC, and QRI. As an example, Figure 4 shows the residuals plotted against the average Pearson correlation coefficient values for MOVE in the east region. The box plots suggest that there is little dependence of the magnitude and sign (i.e. BIAS) of the residual on the value of the Pearson correlation coefficient values. The residuals from the MOVE, BFC, and QRI in both the east and west regions follow this behaviour. The central region had an insufficient amount of streamgages to perform this

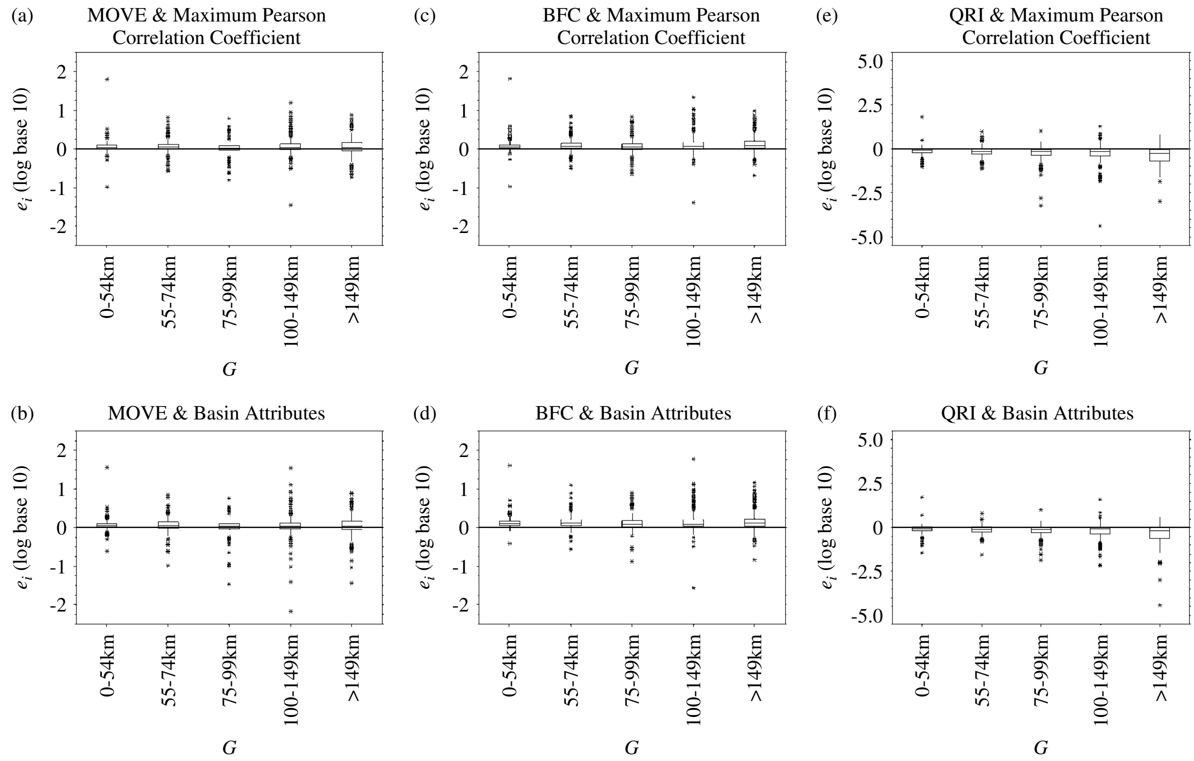

Figure 3. Residual, e_i, as a function of the density of the streamgage network, G, for all regions. The different panels reflect the different combination of criteria to select an index streamgage and the information-transfer approaches used in the index-streamgage approach. The number of streamgages in the 0–54, 55–74, 75–99, 100–149, and > 149 km bins are 230, 228, 203, 236, and 148, respectively

Table I. Values of the mean Pearson correlation coefficient, ρ, standard deviation of ρ, failure rate, and percentage of index-streamgage residuals larger than those from a multiple linear regression (MLR), for all regions using different index-streamgage selection criteria of the maximum Pearson correlation coefficient and basin attributes, BA

Index-streamgage criteria	Range of streamflows (exceedance probabilities)	Mean Pearson correlation coefficient, ρ	Standard deviation of ρ	Failure rate (%)	Percentage of index-streamgage residuals $\geq$ MLR residuals		
					MOVE	BFC	QRI
			East region				
Maximum ρ	50–100	0·86	0·15	5·18	11·44	11·88	25·32
	90–100	0·77	0·23	6·15	6·55	6·84	20·39
BA	50–100	0·63	0·28	5·18	14·20	16·88	21·25
	90–100	0·36	0·44	6·04	7·52	9·28	16·14
			Central region				
Maximum ρ	50–100	0·75	0·20	6·06	17·19	19·07	28·57
	90–100	0·64	0·30	9·04	10·19	9·98	29·58
BA	50–100	0·52	0·33	6·06	16·80	23·22	19·92
	90–100	0·29	0·47	9·46	10·54	10·14	24·07
			West region				
Maximum ρ	50–100	0·75	0·20	6·06	7·02	7·07	19·85
	80–100	0·65	0·27	7·47	5·37	5·18	16·95
BA	50–100	0·52	0·33	6·06	7·54	8·78	16·98
	80–100	0·29	0·47	9·03	6·02	5·74	12·52

Only the optimum range of streamflows defined by the exceedance probabilities and the 50–100% range are reported for each region.

analysis, so comparisons of this region are not made with the other regions.

The parameter and R^2 values from the regional multiple linear regressions are listed in Table II. For the east and central regions, the A_d, τ, and the basin-averaged mean annual precipitation are significant predictors. The west region also includes an additional predictor that measures the mean snow percentage of total precipitation, S. The multiple linear regressions provide the baseline for comparison to the residuals associated with the index-streamgage approach using MOVE, BFC, and QRI. The RMSE values of the regressions are shown as horizontal lines in Figure 2 for only the optimal ranges in each region. The residuals of the index-streamgage approach are deemed a failure if the residuals calculated are larger than or equal to the RMSE value of the corresponding

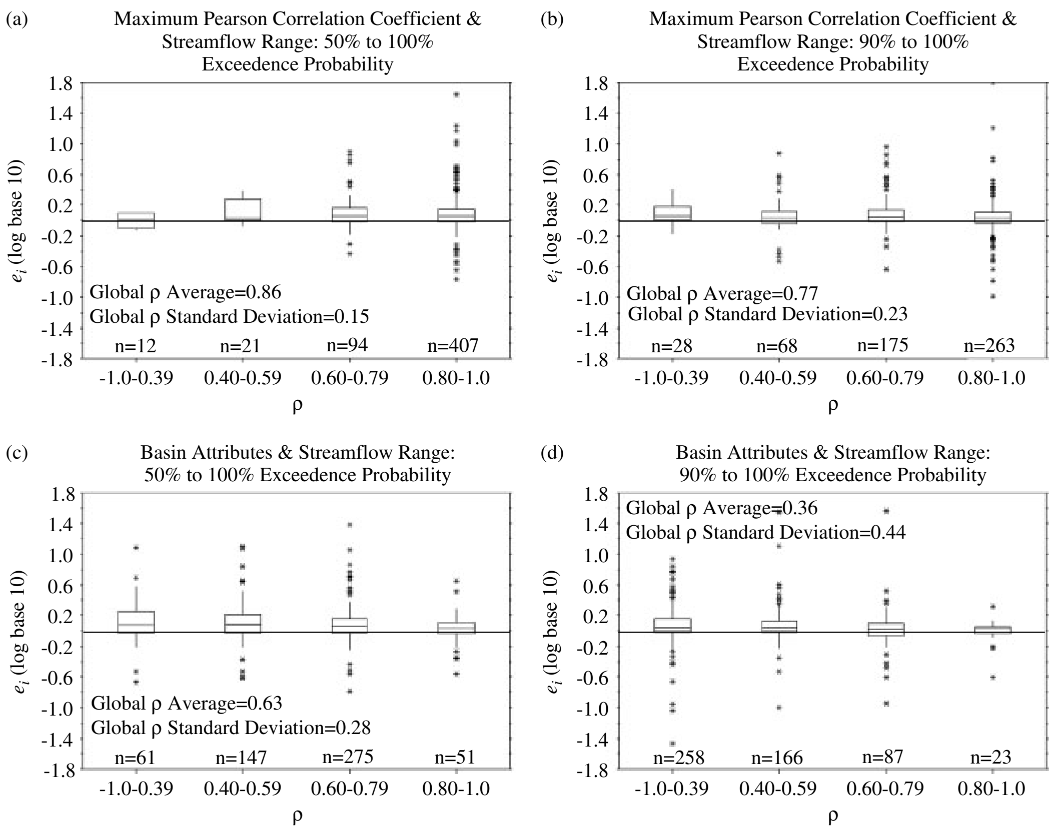

Figure 4. Residual, e_i, as a function of the Pearson correlation coefficient, ρ, among concurrent streamflow values for the MOVE approach in the east region. The different panels reflect the different combination of criteria to select an index streamgage and the range of streamflow values used in the index-streamgage approach

Table II. Values of the multiple linear regression parameters for Equation (3)

Range of streamflows (exceedance probabilities)	Multiple linear regression parameters					R^2
	β_0	β_{Ad}	β_τ	β_P	β_S	
East region						
50–100	−8·66	0·92	2·51	1·61	—	0·78
90–100	−6·43	0·82	1·93	1·04	—	0·75
Central region						
50–100	−13·48	0·90	3·21	3·13	—	0·73
90–100	−8·55	0·75	2·38	1·54	—	0·72
West region						
50–100	−9·74	1·00	1·36	2·36	0·72	0·82
80–100	−8·46	0·97	1·08	1·98	0·70	0·80

The R^2 is equal to the coefficient of determination. The A_d is the drainage area, τ the base-flow recession time constant, P the mean annual precipitation, and S the mean snow percentage of total precipitation. The RMSE values of these regressions are shown in Figure 2.

multiple linear regression. Percentages of these failures are listed in Table I. The east and central regions had larger percentage of failures than the west region. For all regions and both criteria for selection of an index streamgage, the failure rates increase as the range in streamflow values decrease.

The streamgages used in this study are placed into six subsets based on the magnitude of $Q_{7,10}$ calculated from the full record at each station. The arithmetic averages of the residuals for these subsets are shown in Figure 5 for cases in the east region in which basin-attribute similarity was used for index-streamgage selection and only streamflow values between 90 and 100% exceedance probability are used to define the concurrent streamflow relationship between the partial-record and index streamgages. Two of the information-transfer approaches, MOVE and BFC, show a marked tendency to overestimate the $\log(Q_{7,10})$ at streamgages where the observed $Q_{7,10}$ value is very small, with considerably smaller bias as observed $Q_{7,10}$ values increase. Using MOVE, e.g. the arithmetic average of BIAS values of streamgages with a $Q_{7,10}$ value >0 and $<0{\cdot}025$ m^3/s is 0·16, approximately 2·6 times the arithmetic average of BIAS values of all streamgages in the east region. The arithmetic average of BIAS values of streamgages with $Q_{7,10}$ values ≥ 1 m^3/s begins to approach zero. For the QRI information-transfer approach, a large negative bias was seen throughout the range of observed $Q_{7,10}$ values.

The BIAS at streamgages with small $Q_{7,10}$ values may result from the exclusion of a metric that measures similarity of intermittency of streamflow values between the partial-record and the index streamgage. The τ variable is a measure of the intermittency of streamflow in a basin, but based on the results from Figure 5, this metric may be insufficient to characterize the intermittency of streamflow in a basin or the weighting used for it in Equation (2) is not defined correctly. This problem is further compounded by the omission of streamgages with

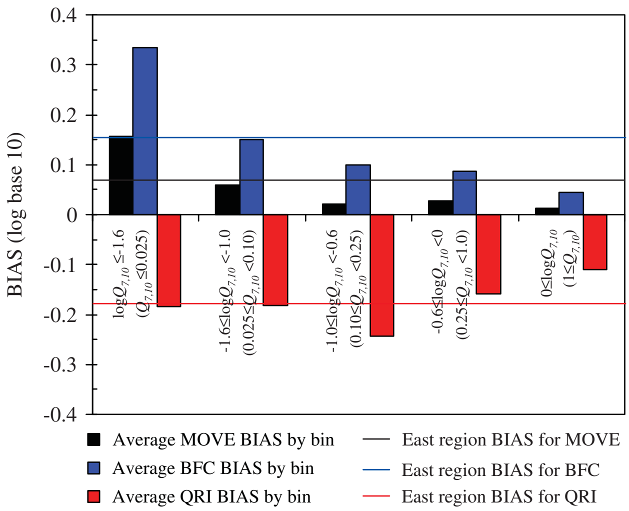

Figure 5. The arithmetic average residual, or BIAS, of the three information-transfer approaches (MOVE, BFC, and QRI) for subsets based on the observed $\log Q_{7,10}$ values (the values in parentheses are the equivalent values in m^3/s). Results are for the east region using similarity of basin attributes to select an index streamgage and restricting streamflows used in the information-transfer approaches to those greater than or equal to the 90% exceedance probability

observed $Q_{7,10}$ values equal to zero, due to the use of log transforms of streamflow values in the MOVE and BFC information-transfer approaches. Selection of an index streamgage for a partial-record streamgage with small $Q_{7,10}$ is limited to those streamgages with less intermittency.

DISCUSSION

The BIAS value for the east region using MOVE and maximum Pearson correlation coefficient to select an index station is 0·12 using the range of streamflow values that lie between the 50 and 100% exceedance-probability streamflows. For the BFC approach, the BIAS is 0·13 using the range of streamflow values between the 50 and 100% exceedance-probability streamflows. These results are similar to those reported by Dingman and Putscher (1991) for 48 basins in New Hampshire and Vermont when restricting concurrent streamflows to those from a summer low-flow period. They reported a BIAS of 0·15 and 0·14 using MOVE and BFC, respectively.

A substantial amount of the over- and underestimation of the $\log(Q_{7,10})$ values is due to the range of streamflow values used in index-streamgage approaches. Our results also show that the density of the streamgage network and index-streamgage selection criteria have small impact on the tendency of index-streamgage approaches to over- or underestimate $\log(Q_{7,10})$ values. On the basis of these results, the index-streamgage approaches using MOVE and BFC are suggested to be applied to three optimal ranges of streamflow values that minimize both BIAS and RMSE values: those associated with 90–100% exceedance-probability flows for the east and central regions and 80–100% exceedance-probability flows for the west region. These suggested ranges of streamflow values may be different for estimated low-flow characteristics other than the $Q_{7,10}$.

The differences in the optimal range of streamflow values among the three regions may be associated with the differences in the median recession lengths. The median recession segment-length values for the east, central, and west are 14·6, 16·0, and 18·1 days, respectively. The IQR values for the east, central, and west are 1·2, 2·5, and 3·5 days, respectively. In general, a larger proportion of the streamflow record for a western basin undergoes a longer state of base-flow conditions than a basin from the east or central regions, so that there is less variability in flows within the 90–100% range. In a number of cases in the west region, the range of streamflows in the 90–100% range was so severely restricted that it was not possible to establish a meaningful relationship between the concurrent streamflows. For the west region, restricting flows to the 90–100% range increases the RMSE from the 80 to 100% case. As a consequence, it is suggested that more of the streamflow record be used in the index-streamgage approach for western basins in order to achieve optimal results.

When BIAS is compared to observed $Q_{7,10}$ values, the results indicate that it may be highly problematic to utilize either the MOVE or BFC information-transfer approaches at synthetic partial-record streamgages where the observed $Q_{7,10}$ value is small. The severe BIAS seen in these cases is likely caused by our omission of streamgages with observed $Q_{7,10}$ values equal to zero, and the lack of an appropriate metric for measuring similarity of intermittency of streamflows among basins. At the time of this study (2010), there is no consensus on how to incorporate streamflow values and characteristics equal to zero in the index-streamgage approach. In actual application of an index-streamgage approach, streamgages with numerous zeros in the daily-streamflow record are commonly excluded from consideration as index streamgages because of the difficulties presented by these zeros (Ries and Friesz, 2000; Funkhouser *et al.*, 2008). On the basis of the bias seen in these results, the need appears to be acute for approaches that allow use of time series with zeros if index-streamgage approaches are to be accurate at partial-record streamgages that approach intermittency. Empirical functions for each region can be developed from relationships shown in Figure 5 to remove the bias using the conventional index-streamgage approaches, but these functions would depend on the assumption that the streamgage network used in future applications will create similar levels of bias as was seen in this study. A more thorough treatment of intermittency could yield non-empirical approaches to remove the bias.

As shown in this study, most of the BIAS values for MOVE, a large portion for BFC, and a substantial portion for QRI are explained. The QRI approach could be consistently biasing, because it includes the origin point in the concurrent streamflow relationship and this constrains the lower end of the curve. A user of the BFC approach assumes that the skew, which is affected by the intermittency of streamflow values, of the annual time series at the index and the partial-record streamgages are the same. Large differences in the intermittency of streamflow values may lead to systematic over- or underestimation of the $Q_{7,10}$ values using BFC. This behaviour is suggested in Figure 2, where the BIAS values of the central region are seen to be larger than those from the other two regions.

Overall, the results indicate that the MOVE and BFC index-streamgage methods are good alternatives to multiple linear regression for estimating $Q_{7,10}$ at sites with limited streamflow information. BIAS in these results can be minimized by restricting the range of flows used when applying the methods. However, care should be taken for streams that approach intermittency, as substantial BIAS may remain.

ACKNOWLEDGEMENT

The authors thank the two anonymous reviewers, Jery R. Stedinger, Kernell Ries, and Charles Parrett for their helpful comments on this article.

REFERENCES

Dingman SL, Putscher JS. 1991. *Applicability of Concurrent Base-Flow Measurement for Estimation of Low-Flow Statistics in New Hampshire and Vermont*. Water Resources Research Center, University of New Hampshire: Durham, NC, New Hampsire, http://www.wrrc.unh.edu/pubs/research%20reports.html. [accessed: 3 January 2011].

Eng K, Milly PCD. 2007. Relating low-flow characteristics to the base flow recession time constant at partial record stream gauges. *Water Resources Research* **43**: W01201. DOI: 10.1029/2006WR005293.

Falcone JA, Carlisle DM, Wolock DM, Meador MR. 2010. GAGES (Geospatial Attributes of Gages for Evaluating Streamflow): A streamgage database for evaluating natural and altered flow conditions in the conterminous United States. *Ecology* **91**(2): 621.

Funkhouser JE, Eng K, Moix MW. 2008. Low-flow characteristics and regionalization of low-flow characteristics for selected streams in Arkansas. U.S. Geological Survey Scientific Investigations Report 2008–5065; 161. http://pubs.usgs.gov/sir/2008/5065/. [accessed: 3 January 2011].

Hirsch RM. 1982. A comparison of four streamflow record extension techniques. *Water Resources Research* **18**(4): 1081–1088.

Kennard MJ, Mackay SJ, Pusey BJ, Olden JD, Marsh N. 2010. Quantifying uncertainty in estimation of hydrologic metrics for ecohydrological studies. *River Research and Applications* **26**: 137–156.

Laaha G, Blöschl G. 2005. Low flow estimates from short stream flow records—a comparison of methods. *Journal of Hydrology* **306**: 264–286.

Loaiciga HA. 1989. Variability of empirical flow quantiles. *Journal of Hydraulic Engineering, American Society of Civil Engineers* **115**(1): 82–100.

Montgomery DC, Peck EA, Vining GG. 2001. *Introduction to Linear Regression Analysis*, 3rd edn. John Wiley & Sons, Inc.: New York; 641.

Potter KW. 2001. A simple method for estimating baseflow at ungauged stations. *Journal of the American Water Resources Association* **37**(1): 177–184.

Reilly CF, Kroll CN. 2003. Estimation of 7-day, 10-year low-streamflow statistics using baseflow correlation. *Water Resources Research* **39**(9): 1236. DOI: 10.1029/2002WR001740.

Ries KG III, Friesz PJ. 2000. Methods for estimating low-flow statistics for Massachusetts streams. U.S. Geological Survey Scientific Investigations Report 00–4135; 81. http://pubs.usgs.gov/wri/wri004135/. [accessed: 3 January 2011].

Riggs HC. 1980. Characteristics of low flows. *Journal of Hydraulics Division, American Society of Civil Engineers* **106**(HY5): 717–731.

Searcy JK. 1959. Flow-duration curves, manual of hydrology-Part 2. Low-flow techniques. United States Geological Survey Water-Supply Paper 1542-A; 1–33. http://pubs.er.usgs.gov/djvu/WSP/wsp_1542-A.djvu. [accessed: 3 January 2011].

Stedinger JR, Thomas WO Jr. 1985. Low-flow frequency estimation using base-flow measurements. U.S. Geological Survey Open-File Report 85–95; 22. http://pubs.er.usgs.gov/djvu/OFR/1985/ofr_85_95.djvu. [accessed: 3 January 2011].

Tasker GD. 1987. A comparison of methods for estimating low flow characteristics of streams. *Water Resources Bulletin* **23**(6): 1077–1083.

Thomas DM, Benson MA. 1970. Generalization of streamflow characteristics from drainage-basin characteristics. U.S. Geological Survey Water Supply Paper 1975; 55. http://pubs.er.usgs.gov/djvu/WSP/wsp_1975.djvu. [accessed: 3 January 2011].

United States Geological Survey. 1979. Programs and plans—low-flow programs. Surface Water Branch Technical Memorandum No. 79·06; United States Geological Survey: http://water.usgs.gov/admin/memo/SW/sw79·06.html. [accessed: 3 January 2011].

United States Geological Survey. 1985. Programs and plans—low-flow frequency estimation at partial-record sites. Surface Water Branch Technical Memorandum No. 86·02. United States Geological Survey: http://water.usgs.gov/admin/memo/SW/sw86·02.html. [Last accessed 01 March 2011].

Zhang Z, Kroll C. 2007. Closer look at the baseflow correlation method. *Journal of Hydraulic Engineering, American Society of Civil Engineers* **12**(2): 190–196.